

*DIVIDED STIMULUS CONTROL: A REPLICATION AND A QUANTITATIVE MODEL*

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Four pigeons were trained on a conditional discrimination. The conditional stimuli were compounds of pairs of stimuli from two different dimensions, fast versus slow cycles of red or green stimuli, and short-versus long-duration presentations of these cycles. Across conditions, the probability of reinforcers for correctly responding to each dimension was varied from 0 to 1. Discriminability, measured by  $\log d$ , for stimuli on a dimension increased as the relative frequency of reinforcers for that dimension increased, replicating the results of Shahan and Podlesnik (2006). Two further conditions showed that discriminability between stimuli on each dimension was unaffected by whether the stimuli on the other dimension varied or were constant. Finally, maximal discriminability was unchanged in a redundant–relevant cues condition in which either of the stimuli comprising a compound signaled the same correct response. Davison and Nevin's (1999) model provided an excellent quantitative account of the effect of relative reinforcer frequency on discriminability, and thus of the way in which divided stimulus control is itself controlled by relative reinforcement.

*Key words:* conditional discrimination, compound stimuli, relative reinforcers, stimulus control, key peck, pigeons

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In a typical conditional-discrimination procedure, two different stimuli signal different contingencies of reinforcement for a subsequent choice. Davison and Tustin (1978) showed how choice in such procedures could be understood in quantitative terms by adding a further bias term ( $\log d$ ) to the generalized-matching law (Baum, 1974). This additive term is called “discriminability”, and it measures how well the animal discriminates between the conditional stimuli. While this quantitative approach has been considerably refined (e.g., Davison & Nevin, 1999), the general notion that choice in such procedures is a joint function of conditional-stimulus discriminability and relative reinforcers for choices has been sustained. Shahan and Podlesnik (2006) applied the same approach to divided stimulus control between the dimensional elements of compound stimuli. They asked whether the relative control by

conditional stimuli on two different stimulus dimensions depended on the relative frequency of reinforcers for correct responses related to the dimensions—would animals make more correct responses following a pair of stimuli from the dimension that provided the higher rate of reinforcers compared to a dimension that provided the lower rate of reinforcers? More generally, is the division of stimulus control (or attention) controlled by relative reinforcer frequency?

Shahan and Podlesnik (2006) used a conditional-discrimination procedure in which two compound stimuli made up from pairs of stimuli from two different dimensions were presented as the conditional stimuli. They used two colors (blue vs. green) and two line orientations (vertical vs. horizontal), presenting a pair (e.g., blue and vertical) on a trial. After 5 s, either the two colors or the two line orientations, chosen with equal probability, were presented on the side keys. A correct response to either the previously presented color on color trials, or to the previously presented line orientation on line trials, was reinforced with a probability of .5. Incorrect choices, and unreinforced correct choices, resulted in a 2-s blackout. A 10-s intertrial interval separated trials. In the experiment, Shahan and Podlesnik varied the ratio of reinforcement for correct responses on color versus line trials from 1:9 through 9:1. They found that the probability of correctly report-

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ing each of the elements of the compound conditional stimulus (measured by discriminability,  $\log d$ , Davison & Tustin, 1978) depended on the probability of reinforcers for correctly reporting those elements. Shahan and Podlesnik interpreted their results as demonstrating that the division of attention to the two dimensions—the relative likelihood that each dimension controls choice—was a function of the relative frequency of reinforcers for correct responses to the dimensions.

The present experiment was a systematic replication and extension of Shahan and Podlesnik's (2006) research but using a symbolic, rather than an identity, matching-to-sample procedure. We also attempted to model our data using the conditional-discrimination model of Davison and Nevin (1999). We reasoned this way: In Shahan and Podlesnik's study, if one of the two stimulus dimensions (e.g., color) was attended to in the sample phase, and remembered until the choice phase, but the other dimension (line) was presented at choice, the pigeons would occasionally obtain a reinforcer by responding to a line that had been ignored on that trial. Such a reinforcer would be nondifferential with respect to the remembered conditional stimulus. Because the color and line choice trials were equally frequent, reinforcers that were nondifferential with respect to the remembered stimulus would occur more often when the probability of reinforcement for correct responses to the other stimulus dimension was greater. The situation, thus, is similar to a "reinforcement-for-errors" procedure (Davison & McCarthy, 1980; Davison & Nevin, 1999; Nevin, Jenkins, Whittaker, & Yarensky, 1982) in which the frequency of reinforcers that were nondifferential with respect to the conditional stimuli is manipulated. Davison and Nevin showed that their model described performance in such procedures very well: Could divided dimensional-stimulus control results be similarly described? In the divided-attention procedure, reinforcers that are nondifferential with respect to one dimensional stimulus pair are differential with respect to the other stimulus pair, whereas in the "reinforcers for errors" procedure, nondifferential reinforcers are nondifferential with respect to any conditional stimuli.

A further reason for looking for an alternative model for divided dimensional control is

	$B_1$	$B_2$
<b>S1</b>	$B_{11}, R_{11}$	$B_{12}$
<b>S2</b>	$B_{21}$	$B_{22}, R_{22}$

Fig. 1. The matrix of events in the standard conditional-discrimination procedure. Conventionally, response  $B_1$  following S1 ( $B_{11}$ ), and  $B_2$  following S2 ( $B_{22}$ ) are correct responses and are reinforced ( $R_{11}$ ,  $R_{22}$  respectively). Responses  $B_{12}$  and  $B_{21}$  are errors and conventionally lead to no reinforcers. However, in a reinforcers-for-errors procedure,  $B_{12}$  and  $B_{21}$  are reinforced ( $R_{12}$  and  $R_{21}$  respectively).

that the model that Shahan and Podlesnik (2006) offered to describe their results cannot be correct. The model is given by their Equation 3, reproduced here:

$$\log d_c - \log d_l = a \log \frac{R_c}{R_l} + \log b. \quad (1)$$

In this equation, the subscripts  $c$  and  $l$  refer to color and line, respectively. The measures  $R_c$  and  $R_l$  refer to the frequency of reinforcers for color and line correct discriminations,  $a$  is sensitivity to reinforcement, and  $\log b$  is bias (Baum, 1974).  $\log d_c$  and  $d_l$  are point estimates of discriminability for color and line, respectively, obtained from Davison and Tustin's (1978) model:

$$\log d_i = 0.5 \log \frac{B_{11} B_{22}}{B_{12} B_{21}}, \quad (2)$$

where the subscript  $i$  refers to either color or line discriminability, and  $B$  to the responses in the matrix shown in Figure 1. The problem with Equation 1 is that, for any particular pair of stimuli on a dimension,  $\log d$  has a minimum value of 0, and a maximum value that is less than infinity unless the conditional stimuli are perfectly discriminable. Thus, unlike the prediction of Equation 1,  $(\log d_c - \log d_l)$  must be less than infinity when  $R_l$  is zero and  $\log d_c$  is less than infinite. Additionally, if only correct responses to a single dimension are reinforced as in the standard conditional-discrimination procedure, the reinforcer ratio,  $R_c/R_l$  is either infinite, or zero, depending on the relevant dimension. Thus, while Shahan and Podlesnik showed a convincing linear relation between relative accuracy and  $\log (R_c/R_l)$  (their Figure 2), this relation must fail for the standard conditional-

discrimination procedure when there are no reinforcers for one of the discriminations. Shahan and Podlesnik did not conduct any conditions with either  $R_c$  or  $R_l = 0$ , so did not face this problem with their model. Evidently, a revised model is required. The present experiment collected data at both these extreme log reinforcer ratios.

Shahan and Podlesnik's (2006) model was based on the generalized-matching relation (Baum, 1974). The problem that the model (Equation 1) has may result from the generalized-matching model itself being unable to describe choice accurately when the reinforcer rate for one alternative is zero. Davison and Jones (1998) investigated performance on concurrent VI Extinction schedules and found that choice was constant, less than infinite, and independent of the reinforcer rate arranged on the VI schedule. Davison and Jones' results were predictable from an alternative model of choice, the contingency-discriminability model (Davison & Jenkins, 1985) which forms the basis of the conditional-discriminability model discussed by Davison and Nevin (1999). As this model was used by Davison and Nevin to account for performance in "reinforcers for errors" procedures, we were interested to see whether it could account for data from divided stimulus control experiments.

## METHOD

### *Subjects*

Four homing pigeons numbered 161 to 164 were kept at 85% of their free-feeding body weights. They had extensive experience, most recently on concurrent schedules with various sorts of feedback functions. They had continuous access to grit and water at all times.

### *Apparatus and Procedure*

The pigeons worked in their home cages, which were 300 mm high  $\times$  300 mm wide  $\times$  300 mm deep, in a laboratory in which the lights were turned on at 12 midnight, and off at 4 pm. The session for all pigeons started at 2 am and was signaled by the illumination of the first compound stimulus. We used two stimulus dimensions presented on the center key of the three-key interface: The first was red/green colored key lights alternating every 0.1 s or every 0.5 s (10 Hz or 2 Hz, which we will

term Fast and Slow respectively); the second was the duration with which the fast/slow alternating colors were presented on the center key, 10 s (Long) and 2 s (Short). All four pairs of stimuli, comprising one from each dimension, selected randomly ( $p = .5$  Fast/Slow,  $p = .5$  Long/Short), could be presented as conditional stimuli. Thus, the conditional stimuli were one of: fast red/green cycles lasting 2 s; fast red-green cycles lasting 10 s; slow red/green cycles lasting 2 s; and slow red/green cycles lasting 10 s. No observing response was required. Following the presentation of the compound stimulus, the center key was extinguished, and two white side keys were illuminated. Reinforcers (2-s access to wheat) were available for correct responses, left correct for Fast or Long, and right correct for Slow or Short. However, the dimension for which a correct response would be reinforced was determined probabilistically, and reinforcers set up for a correct response were held until that reinforcer had been obtained. Thus, a reinforcer could be arranged for a left response given a Long stimulus, and this was held until such a left response was made—which, for example, might be following a Long-Fast stimulus presentation, or following a Long-Slow stimulus presentation. If a reinforcer was not available for the choice emitted, there was a 2-s blackout, and trials were separated by a further 10-s blackout with key lights extinguished and responses inoperative.

The probability of reinforcers for correct responses following the Long-Short (LS) dimension,  $p(Rf|LS)$ , was varied over seven levels from 0 to 1 in quasirandom order, with  $p(Rf|FS)$  (Fast-Slow) the complement of these values (see Table 1). Thus,  $p(Rf|LS) = 0$  is an arrangement in which only correct responses following Fast-Slow stimuli are reinforced. The condition  $p(Rf|LS) = .5$  is a condition in which correct Fast-Slow responses are as likely to be reinforced as correct Long-Short responses. In each condition, we counted the number of Left and Right choices and the number of reinforcers obtained following each of the four combinations of stimuli that were presented.

Three further conditions were conducted. In Conditions 8 and 9, only one stimulus dimension was relevant to choice. In Condition 8, we arranged Fast-Slow Red-Green

Table 1

Sequence of experimental conditions and the probability of reinforcers for correct responses to the Long–Short discrimination,  $p(\text{RfLS})$ .  $p(\text{RfFS})$  was the complement of  $p(\text{RfLS})$ .

Condition	$p(\text{RfLS})$
1	1
2	.2
3	.9
4	.1
5	.8
6	.5
7	0
8	FS only
9	LS only
10	FS & LS redundant

cycles of 0.1 and 0.5 s (as in Conditions 1 to 7) with correct Fast–Slow choices having a probability of reinforcement of 1.0. The duration of presentation was 4.5 s for both presentations. Condition 9 arranged Long–Short durations of 2 and 10 s (as in Conditions 1 to 7) with correct Long–Short responses having a probability of reinforcers of 1.0; the red/green color alternation frequency was 0.22 s. These conditions were conducted to determine whether stimulus variation on one stimulus dimension affected discrimination of the other dimension. The final Condition 10 was a redundant–relevant cues condition in which only two pairs of stimuli from the two dimensions were ever presented, one pair signaling a left-correct response, the other pair a right-correct response. This condition was conducted to discover whether redundant–relevant cues would produce more accurate discrimination than compounds of cues.

Thirty sessions of training were arranged in each condition, and the last 15 sessions were used in all analyses. Stability on each condition was assessed by inspection of the percentage correct for both of the discriminations. Performance appeared stable by 15 sessions in all conditions.

The effects of changing  $p(\text{RfLS})$  on the programmed reinforcer differential following Fast–Slow stimuli in this procedure are shown in Table 2. Decreasing the probability of reinforcers for correct Long–Short discrimination adds nondifferential reinforcers (spread equally across the detection matrix) for performance following Long and Short stimuli. At the same time, this change increases the

number of reinforcers that are differential with respect to the Fast–Slow discrimination, and decreases the number of nondifferential reinforcers for Fast–Slow discrimination. Another way of describing the effects of changing the probability of reinforcers for a dimension is to note that this probability changes the relevance of a dimension between irrelevant (when the probability of reinforcers for that dimensional discrimination is zero) to relevant (probability of reinforcers = 1), while changing the other dimension from relevant to irrelevant. But notice that these changes are not from redundant relevant cues to irrelevant cues or vice versa, because the choices required for discrimination were different. In redundant relevant cues, two different cues signal the *same* correct choices.

## RESULTS

Estimates of  $\log d$  (Davison & Tustin, 1978) were calculated as point estimates according to Equation 2 for both Long–Short and Fast–Slow discriminations in each condition. Note that each  $\log d$  estimate used all of the eight response counters (four stimulus compounds and two responses) that we recorded. For instance,  $B_{\text{Left}}$  for Long/Short consisted of left responses following Long+Fast and Long+Slow, while  $B_{\text{Left}}$  for Fast/Slow used left responses following Long+Fast and Short+Fast.

Figure 2 shows  $\log d_{\text{LS}}$  and  $\log d_{\text{FS}}$  for all subjects, and the data averaged across subjects, as a function of the probability of reinforcers for correct responses to the Fast–Slow dimension. For all subjects,  $\log d_{\text{LS}}$  increased, and  $\log d_{\text{FS}}$  decreased, progressively as  $p(\text{RfLS})$  increased. A nonparametric trend test (Ferguson, 1971; Kendall, 1955) confirmed these trends at  $p < .05$  ( $z = 5.7$  for LS, 6.7 for FS,  $N = 4$ ,  $k = 7$ ). Discriminability values for LS when  $p(\text{RfLS})$  was 1 were similar to discriminability values for FS when  $p(\text{RfLS})$  was 0, which are the locations at which all reinforcers were differential for Long versus Short and for Fast versus Slow respectively.

A further measure, called response bias or  $\log b$ , can be derived from the Davison-Tustin (1978) model:

$$\log b = 0.5 \log \frac{B_{11}B_{21}}{B_{12}B_{22}}, \quad (3)$$

Table 2

The effects of changes in the probability of reinforcers for correct Fast-Slow responses on reinforcer delivery in the cells of the stimulus-response matrix, assuming a session of 80 reinforcers.

REINFORCERS WITH RESPECT TO <u>FAST/SLOW</u>									
		Rfs from F/S		Rfs from L/S			ALL rfs		
		Ch1	Ch2	Ch1	Ch2		Ch1	Ch2	
$p(\text{RIFS}) = 1$	F	40	0	F	0	0	F	40	0
	S	0	40	S	0	0	S	0	40
$p(\text{RIFS}) = .5$	F	20	0	F	10	10	F	30	10
	S	0	20	S	10	10	S	10	30
$p(\text{RIFS}) = 0$	F	0	0	F	20	20	F	20	20
	S	0	0	S	20	20	S	20	20

*Note.* CH1 and CH2 are the two response choices. Upper row: When the probability of reinforcers for the Fast-Slow discrimination is 1.0, all reinforcers are obtained from correct responses with respect to Fast-Slow, and none from Long-Short. As a result, reinforcers for correct Fast-Slow choices are completely differential with respect to this dimension. Center row: When the probability of reinforcers for the Fast-Slow discrimination is .5, reinforcers for correct Fast-Slow responses are differential with respect to these stimuli, but reinforcers arising from correct Long-Short responses are completely nondifferential with respect to Fast-Slow. As a result, all reinforcers for Fast-Slow (right column) choices are partially differential with respect to this dimension. Bottom row: When the probability of reinforcers for the Fast-Slow discrimination is 0, all reinforcers for Fast-Slow responses are completely nondifferential with respect to Fast-Slow. The situation is exactly reversed for Long-Short choices arranged with a complementary probability.

where the variables are the same as in Equation 2. Log  $b$  is a measure of the relative frequency of left versus right responses, and is theoretically independent of log  $d$ . Because we did not change the relative frequency of left versus right reinforcers in this experiment, we would expect that this measure would not change as a function of  $p(\text{RfLS})$ . Log  $b$  did not change in any systematic way (data not shown), and nonparametric trend tests did not reach significance ( $z = 0.66$  overall,  $N = 8$ ,  $k = 7$ ).

Conditions 8 and 9 arranged that one stimulus dimension was differential while the other was held constant. Discriminability (log  $d$ ) values for these two conditions, and the comparable Conditions 1 and 7, are shown in Figure 3. There was no systematic difference in log  $d$  values between conditions in which stimuli on one dimension were relevant to the conditional discrimination while the other was either varied (Conditions 1 and 7) but irrelevant, or constant (Conditions 8 and 9).

Log  $d$  values from Condition 10, the redundant-relevant cues procedure in which conditional stimuli on either dimension were equally salient, must be compared with the maximum discriminability values from Conditions 8 and 9, because choice might be controlled by either the Fast-Slow stimuli or the Long-Short durations in Condition 10.

Figure 4 shows 95% confidence intervals around median log  $d$  values for Condition 10 and for whichever of Conditions 8 and 9 had the higher discriminability measure (which condition was used is shown in Figure 4). From these confidence intervals, it is clear that there was no significant difference between log  $d$  measured when stimuli on only one dimension were arranged versus when stimuli on both dimensions signaled the same correct responses.

## DISCUSSION

As reported by Shahan and Podlesnik (2006), the degree to which one of a pair of stimulus dimensions controlled choice depended on the degree to which reinforcers were differential with respect to stimuli on that dimension. This control was graded, rather than all-or-none, indicating that each dimension could exert partial stimulus control over choice. The present experiment was a systematic, rather than a direct, replication of the findings of Shahan and Podlesnik: The two experiments differed in a number of ways. First, we replicated their effect with different stimuli: They used color and line-orientation stimuli, we used red-green cycle frequency and stimulus duration. Second, Shahan and Podlesnik used an identity matching-to-sample



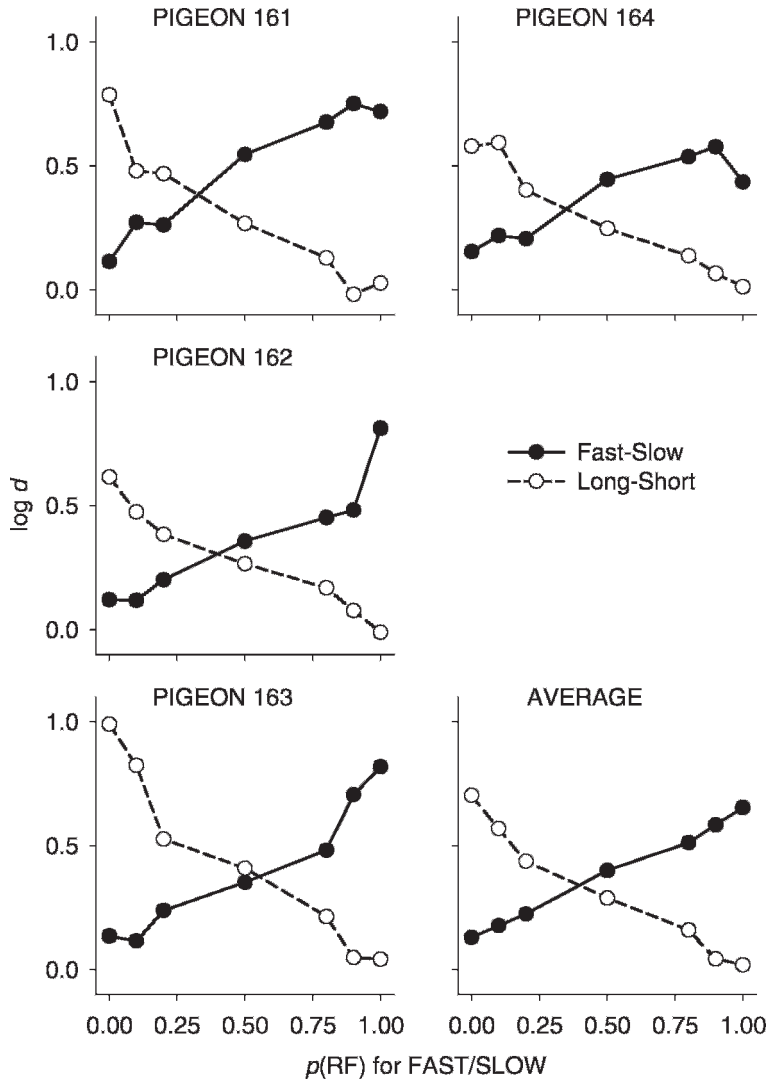


Fig. 2. Point estimates of  $\log d$  for Fast-Slow and Long-Short discrimination for each pigeon and each condition as a function of the probability of reinforcers for Fast-Slow relative to reinforcers for Long-Short. The data for each individual, and for the average across individuals, are shown.

procedure, while this research used a symbolic procedure. Third, and related to the last point, Shahan and Podlesnik gave unidimensional choices—either the two colors on color trials, or the two line-orientation stimuli, but we provided only one type of choice trial (two white keys).

We did not provide a dimension-differential stimulus for retrieval at choice. Thus, our replication of Shahan and Podlesnik’s (2006) finding of graded stimulus control, as a function of the probability of reinforcers for correct reports of stimuli on one dimension

versus the other, strongly rejects any notion that the graded stimulus control resulted from failures of memory retrieval at the choice point. Rather, it suggests simply that the degree of stimulus control of choice by dimension-specific stimuli depended on the frequency of reinforcers for correct responses to that dimension relative to reinforcers for conditional control by the other dimension. Our finding that control over choice was no better when only one dimension was relevant, or both were equally, and redundantly, relevant (Condition 10) to choice suggests that the

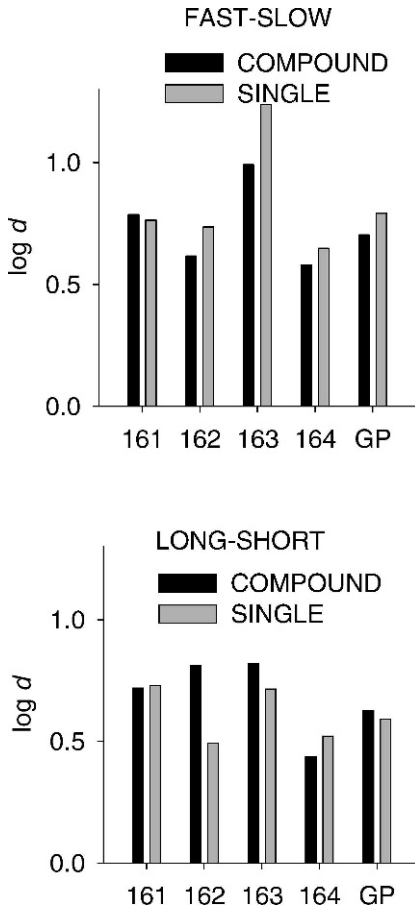


Fig. 3. Comparison of estimates of  $\log d$  from conditions in which both Fast-Slow and Long-Short were varied (Conditions 1 and 7) and conditions in which only Fast-Slow or Long-Short was varied (Conditions 8 and 9). The upper graph (Fast-Slow) compares the results from Conditions 7 and 8, and the lower graph (Long-Short) those from Conditions 1 and 9.

pigeons were not confusing the dimensions when both dimensions were operative.

In Table 2, we displayed the nature of the procedure we used. By changing the probability of reinforcers for correct choices following Long-Short stimuli, we changed the frequency with which reinforcers would have appeared to be nondifferential with respect to the Long-Short conditional stimuli, but differential with respect to the Fast-Slow stimuli. The procedure is thus similar to procedures in which some reinforcers that are nondifferential with respect to the conditional stimuli are explicitly scheduled in a conditional discrimination task.

Research reported using such a task (Davison & McCarthy, 1980; Nevin et al., 1982), shows that estimated values of  $\log d$  fall when the probability of nondifferential reinforcers is increased. This result is incompatible with the theoretical assumption that  $\log d$  is solely a result of stimulus differential, and independent of reinforcer conditions. Early attempts to provide a quantitative model of such results (Davison & McCarthy) that maintained a constant stimulus measure in the face of nondifferential reinforcers failed, but a later approach (Davison & Nevin, 1999), using a model introduced by Alsop (1991) and Davison (1991), was highly successful.

The model that Davison and Nevin (1999) used assumes that reinforcers delivered in any one cell of the signal-detection matrix (see Figure 1) may generalize to other cells, and that the amount of generalization depends inversely on the degree to which the stimuli and the contingencies of reinforcement can be discriminated. If these are highly discriminable, there will be little or no generalization; if they are indiscriminable, there will be complete generalization. Two parameters,  $d_{sb}$  and  $d_{br}$ , respectively measure stimulus-response, and response-reinforcer, contingency discriminability. The model assumes that choice behavior following each of the stimuli strictly matches the "apparent" reinforcers (that is, after the generalization processes) that the animal obtains. Thus, the model for performance following a stimulus in which  $B_L$  is correct is:

$$\text{Following S1: } \frac{B_L}{B_R} = \frac{R_{11} + R_{12}/d_{br} + R_{21}/d_{sb} + R_{22}/d_{sb}/d_{br}}{R_{12} + R_{11}/d_{br} + R_{21}/d_{sb}/d_{br} + R_{22}/d_{sb}}, \quad (4)$$

$$\text{and following S2: } \frac{B_L}{B_R} = \frac{R_{21} + R_{22}/d_{br} + R_{12}/d_{sb}/d_{br} + R_{11}/d_{sb}}{R_{22} + R_{21}/d_{br} + R_{12}/d_{sb} + R_{11}/d_{sb}/d_{br}}. \quad (5)$$

$R_{12}$  and  $R_{21}$ , which are not shown in Figure 1, are reinforcers delivered for "error" choices. Davison and Nevin showed that the Davison and McCarthy (1980) and Nevin et al. (1982) data could be successfully fitted by this model with constant  $d_{sb}$  and  $d_{br}$  values, with high variance accounted for.

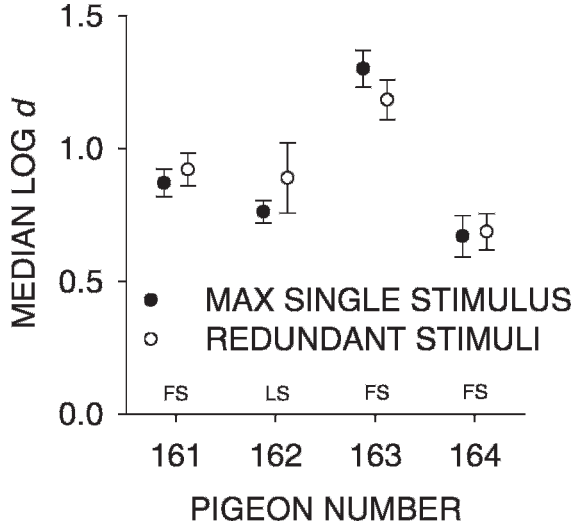


Fig. 4. 95% confidence intervals around median values of log  $d$  for the single-stimulus condition giving the higher log  $d$  value (Max single stimulus), and for the redundant-relevant cues Condition 10. Which single stimulus provided the maximum discriminability (FS or LS) is shown on the graph.

To what extent might Davison and Nevin's (1999) model (Equations 4 and 5) account for the present data? It certainly would predict that Long-Short stimulus response discrimination would fall as  $p(\text{Rf}|\text{LS})$  fell when more non-differential reinforcers were added to the matrix. Thus, we fitted the model based on Equations 4 and 5 for performance after S1 and S2 to the log  $d_{\text{LS}}$  and log  $d_{\text{FS}}$  data shown in Figure 2 simultaneously. We assumed that  $d_{\text{sbLS}}$  could differ from  $d_{\text{sbFS}}$ —that is, the maximum degree to which the Long versus Short stimuli could be discriminated under purely differential reinforcers for Long versus Short was different from that for the Fast versus Slow discrimination. However, we constrained the fit to use the same  $d_{\text{br}}$  value for the two stimulus dimensions as we have no reason to think that  $d_{\text{br}}$  would differ between the two stimulus dimensions. Point estimates of log  $d_{\text{FS}}$  and log  $d_{\text{LS}}$  values that would be expected from Equation 2 were derived from Equations 4 and 5. In the following equation,  $x$  is a placeholder for either Fast-Slow or Long-Short:

$$\log d_x = .5 * \log$$

$$\left( \frac{R_{11} + R_{12}/d_{\text{br}} + R_{21}/d_{\text{sbx}} + R_{22}/d_{\text{sbx}}/d_{\text{br}}}{R_{12} + R_{11}/d_{\text{br}} + R_{21}/d_{\text{sbx}}/d_{\text{br}} + R_{22}/d_{\text{sbx}}} \right) \cdot \frac{R_{22} + R_{21}/d_{\text{br}} + R_{12}/d_{\text{sbx}} + R_{11}/d_{\text{sbx}}/d_{\text{br}}}{R_{21} + R_{22}/d_{\text{br}} + R_{12}/d_{\text{sbx}}/d_{\text{br}} + R_{11}/d_{\text{sbx}}} \quad (6)$$

where  $R_{11}$ , for example, refers to LeftLong reinforcers for the Long-Short analysis, and RightFast reinforcers for the Fast-Slow aspects of the analysis. The fits were done using the QuattroPro® Optimizer, which found the best-fitting, by least squares,  $d_{\text{sbLS}}$ ,  $d_{\text{sbFS}}$ , and  $d_{\text{br}}$  values. The results are shown in Table 3. Variance accounted for by the fits to individual data was between 72% and 94% (mean data 93%), and mean squared deviations between obtained and predicted log  $d$  values were between 0.005 and 0.016 (mean deviation 0.003). The fits were thus very good. The value of  $d_{\text{sbLS}}$  varied between 13.99 and 15.66 for individual data (mean 14.6), and that of  $d_{\text{sbFS}}$  varied between 8.36 and 16.54 (mean 11.32). The values of  $d_{\text{br}}$  varied between 5.52 and 12.29 (mean 7.37). Each of these values is entirely reasonable. We could also have obtained a good fit by assuming that  $d_{\text{sbLS}} = d_{\text{sbFS}}$ , but there is good theoretical reason not to assume this—asymptotic discriminability between pairs of stimuli on different dimensions will naturally be different. We conclude that the Davison and Nevin (1999) conditional discrimination model predicts and understands the present divided stimulus-control data.

Can the same model fit the Shahan and Podlesnik (2006) data? Indeed, were their data also nondifferential reinforcement data? Some discussion is required, because their procedure differed from the one used here. As in



Table 3  
Results of Fitting Equation 6 to Individual and Mean Data from Conditions 1 to 7.

	Pigeon				Mean data
	161	162	163	164	
$d_{sb}(LS)$	16.73	15.66	13.99	14.70	14.60
$d_{sb}(FS)$	11.86	8.36	16.54	8.80	11.32
$d_{br}$	12.29	7.37	11.49	5.52	7.37
Mean Dev	0.016	0.005	0.005	0.010	0.003
VAC	82	92	94	72	93

*Note.* The parameters  $d_{sb}(LS)$  and  $d_{sb}(FS)$  are the best-fitting values of stimulus-response discriminability on the Long-Short and the Fast-Slow dimensions respectively, and  $d_{br}$  is the response-reinforcer discriminability. Mean Dev is the mean deviation between the data and the predictions, and VAC is the percentage of data variance accounted for.

the present experiment, they presented compounds as conditional stimuli, but they presented only stimuli from one dimension (color or line orientation) for choices. How would this be a nondifferential reinforcement procedure? The answer is that if an animal viewed the compound stimulus, and remembered that it was color red, say, what would occur on a subsequent forced choice between two line orientations? A correct response might be emitted by chance, and a reinforcer perhaps obtained. What would the pigeon learn on this trial? The line orientations (or the colors) presented as choices were randomized across the left and right choice keys. Thus, it might learn “saw red, pecked vertical, got a reinforcer”, providing a reinforcer that was nondifferential with respect to color. The procedure used by Shahan and Podlesnik is effectively similar to the procedure used here, and the trends in their data can likely be understood with the model that described the present data.

Making only one of the two stimulus dimensions relevant (that is, reinforcing only correct responses with respect to that dimension) had no blocking or overshadowing effect on control in later conditions when the other stimulus dimension was made more, or fully, relevant. The present results thus support the finding of Wilkie and Masson (1976). These authors showed convincingly that overwhelming stimulus control by one dimension of a compound stimulus did not attenuate, but rather speeded, later learning when the other dimension was made relevant. In our Condition 1, only the Long-Short discrimination was differentially reinforced, and the Fast-Slow discrimination was irrelevant. Nevertheless,

the Fast-Slow dimension quickly acquired control in later conditions in which it was relevant, and there was no evidence of any asymmetry in control by each dimension across the experiment as a whole. In terms of blocking, the most surprising pair of results came from Conditions 1 and 7, in which dimensional control was completely and symmetrically shifted from Fast-Slow to Long-Short.

Findings of graded, divided stimulus control are not new. For instance, in a series of papers, Blough (e.g., 1972), using maintained generalization testing, showed similar divided stimulus control. The first demonstration of overshadowing, or selective stimulus control when two competing dimensions are simultaneously introduced (Reynolds, 1961), showed complete overshadowing of one dimension by another. In transfer tests following training of a successive discrimination between compound stimuli, one of Reynolds’ pigeons responded only to the color element of S+, and almost not at all to any of the other transfer stimuli. His second pigeon responded only to the shape element of S+ and apparently ignored the colors completely. However, Farthing and Hearst (1970) showed control by dimensions of compounds on test trials in which the positive and negative elements from the weaker dimension were compounded with the S+ element from the stronger dimension. Overshadowing was not all-or-none—rather, stimulus control was graded and divided between the two dimensions. The present results, with those discussed above, show that partial, divided, stimulus control is common. With Shahan and Podlesnik’s (2006) results, they show further that this division of stimulus

control is itself controlled by the probability of reinforcement for correct discriminations on each dimension.

A number of other results may represent divided stimulus control, and in some of these, the division may be between control by external stimuli and control by contingencies of reinforcement. Consider, for example, a conditional discrimination in which the conditional stimuli and the reinforcer contingencies are highly discriminable. A stimulus may signal that a left-key response will be correct, but the reinforcer conditions may have more reinforcers for correct right-key than left-key responses (e.g., Jones, 2003). What's a bird to do? Alternatively, if the conditional stimuli are only marginally discriminable, we may expect enhanced reinforcer control. The Davison and Nevin (1999) model may be able to understand these procedures as nondifferential reinforcement procedures.

In conclusion, should we think of the procedures of Shahan and Podlesnik (2006) and that used here as measuring divided attention or divided stimulus control? Certainly, the choice behavior measured is similar to that which, in other areas, would be seen as evidence and measures of attention, and terming this behavior as "attention" helps us connect with other areas. The problem for us in using "attention" is the implication that something in the organism is reaching out to "feel" an exteroceptive stimulus (or even "feeling" in to reach an interoceptive stimulus). The only evidence for such a process comes from stimulus control and divided stimulus control. But, then, how should we think of choice that is partially controlled by two different stimulus dimensions? Such partial control is affected by both (a), the psychophysics of the environmental stimuli on each dimension, which determines how well the pairs of stimuli can be discriminated; and (b), a further, apparently organismic, process that attenuates this environmental control. Calling this latter effect "attention" or "differential filtering" does feel satisfactory, at least as a shortcut, but it is not the whole explanatory story. Within the Davison and Nevin (1999) model that we have used to account for divided stimulus control, there is no requirement for a stand-alone attention process—the degree of divided attention is entirely accounted for by the relative reinforc-

ers obtained on the two dimensions. Indeed, the attentional models of Nevin et al. (2005, 2007) are unable to account for the present data without setting one parameter value in their model to an unusual value<sup>1</sup>, and the present data can be accurately modeled without invoking these more complex models. Attention, then, is simply differential reinforcement with respect to different sets of, or dimensions of, stimuli.

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